IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15480

BRAIN-COMPUTER INTERFACE SYSTEMS USING ARTIFICIAL INTELLIGENCE: A REVIEW OF EEG-BASED APPROACHES

Vidya K T [1], Rajeshwari N [2]

Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India[1,2]

Abstract: Brain–Computer Interface (BCI) systems enable direct communication between the human brain and external devices by interpreting neural signals, primarily captured through Electroencephalography (EEG). With the increasing demand for assistive technologies, healthcare monitoring, and intelligent human–machine interaction, EEG-based BCI systems have gained significant attention in recent years. However, the inherent complexity, noise, and variability of EEG signals pose major challenges in achieving accurate and reliable signal classification.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML), particularly deep learning techniques, have significantly improved the performance of EEG-based BCI systems. Models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), hybrid CNN–LSTM architectures, and attention-based models have demonstrated strong capability in extracting spatial and temporal features from EEG signals.

This paper presents a comprehensive review of recent research developments (2020–2026) in AI-driven EEG-based BCI systems. It analyzes various models, techniques, and challenges, and highlights future research directions for improving system accuracy and real-time applicability.

I. INTRODUCTION

Brain–Computer Interface (BCI) systems represent an advanced technology that enables direct communication between the human brain and external devices without relying on traditional neuromuscular pathways. By capturing and interpreting neural activity, BCI systems provide an alternative communication channel, particularly for individuals with motor impairments and neurological disorders. Among various signal acquisition techniques, Electroencephalography (EEG) is widely used due to its non-invasive nature, cost-effectiveness, and ease of implementation.

EEG-based BCI systems operate by recording electrical signals from the brain through electrodes placed on the scalp and converting these signals into meaningful commands using signal processing and classification techniques. These systems have been widely applied in areas such as assistive technologies, neurorehabilitation, emotion recognition, and smart environments. To provide a clear understanding of the working mechanism, the general architecture of an EEG-based BCI system is illustrated in Fig. 1.

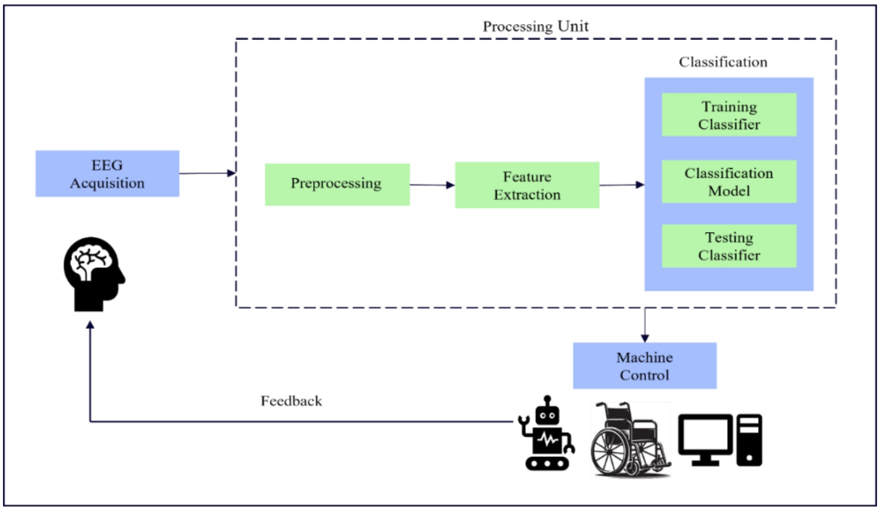

Fig. 1. General architecture of an EEG-based Brain–Computer Interface system

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15480

Despite their wide range of applications, EEG-based BCI systems face several challenges due to the complex nature of brain signals. EEG signals are highly susceptible to noise, non-stationary behaviour, and variability across different individuals and sessions. These factors make accurate signal classification difficult and limit the performance of conventional approaches. Traditional machine learning techniques often rely on manual feature extraction, which requires domain expertise and may not generalize well across different datasets.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML), particularly deep learning techniques, have significantly improved the performance of EEG-based BCI systems. Models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), hybrid CNN–LSTM architectures, and attention-based models have demonstrated strong capability in automatically extracting spatial and temporal features from EEG signals, leading to improved classification accuracy in various BCI applications.

This paper presents a comprehensive review of recent advancements in AI-driven EEG-based BCI systems from 2020 to 2026. It analyzes different deep learning models, signal processing techniques, and hybrid approaches used for EEG classification. In addition, key challenges such as signal variability, data scarcity, and real-time implementation constraints are discussed, along with potential future research directions for developing more efficient and robust BCI systems.

II. LITERATURE SURVEY

Recent advancements in EEG-based Brain–Computer Interface (BCI) systems have been significantly influenced by the integration of Artificial Intelligence (AI) and deep learning techniques. Traditional machine learning methods relied on manual feature extraction and statistical approaches, which were limited in handling complex and non-linear EEG signals. Recent studies demonstrate that deep learning models provide improved feature extraction and classification performance across various BCI applications, achieving higher accuracy and robustness compared to conventional methods [1], [2], [3], [5].

A. CNN-Based EEG Classification

Convolutional Neural Networks (CNNs) have become one of the most widely used models for EEG signal classification due to their ability to automatically extract spatial features from raw EEG data. Architectures such as EEGNet and deep CNN models have shown strong performance in motor imagery and emotion recognition tasks.

Several studies report that CNN-based models achieve classification accuracy in the range of **80% to 85%** on standard EEG datasets [3], [16], [17]. Lightweight CNN architectures have also been proposed to reduce computational complexity, making them suitable for real-time BCI applications [11]. Despite their effectiveness, CNN models may struggle to capture temporal dependencies in EEG signals.

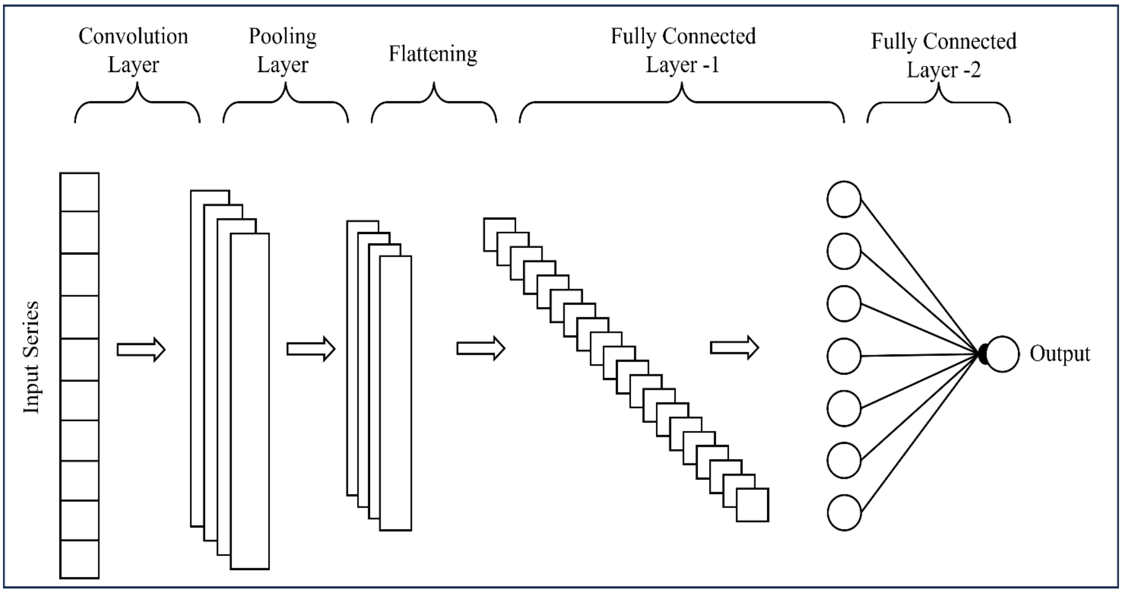

Fig. 2. Basic architecture of a Convolutional Neural Network (CNN).

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15480

B. LSTM and Temporal Models

Long Short-Term Memory (LSTM) networks are specifically designed to model sequential data and capture temporal dependencies. Since EEG signals vary over time, LSTM models are well-suited for analyzing time-series brain signals. Studies indicate that LSTM-based approaches achieve classification accuracy of approximately **75% to 85%**, depending on the dataset and application [2], [9]. These models are particularly useful in tasks such as emotion recognition and continuous brain monitoring. However, LSTM models often require longer training time and higher computational resources.

C. Hybrid CNN–LSTM Models

Hybrid models combining CNN and LSTM architectures have shown superior performance by leveraging both spatial and temporal feature extraction. In these models, CNN layers extract spatial features from EEG signals, while LSTM layers capture temporal dependencies.

Research shows that hybrid CNN–LSTM models achieve higher classification accuracy, typically in the range of **85% to 90%**, outperforming standalone CNN or LSTM models [4], [13], [22]. These models are widely used in motor imagery classification and have demonstrated improved robustness and generalization.

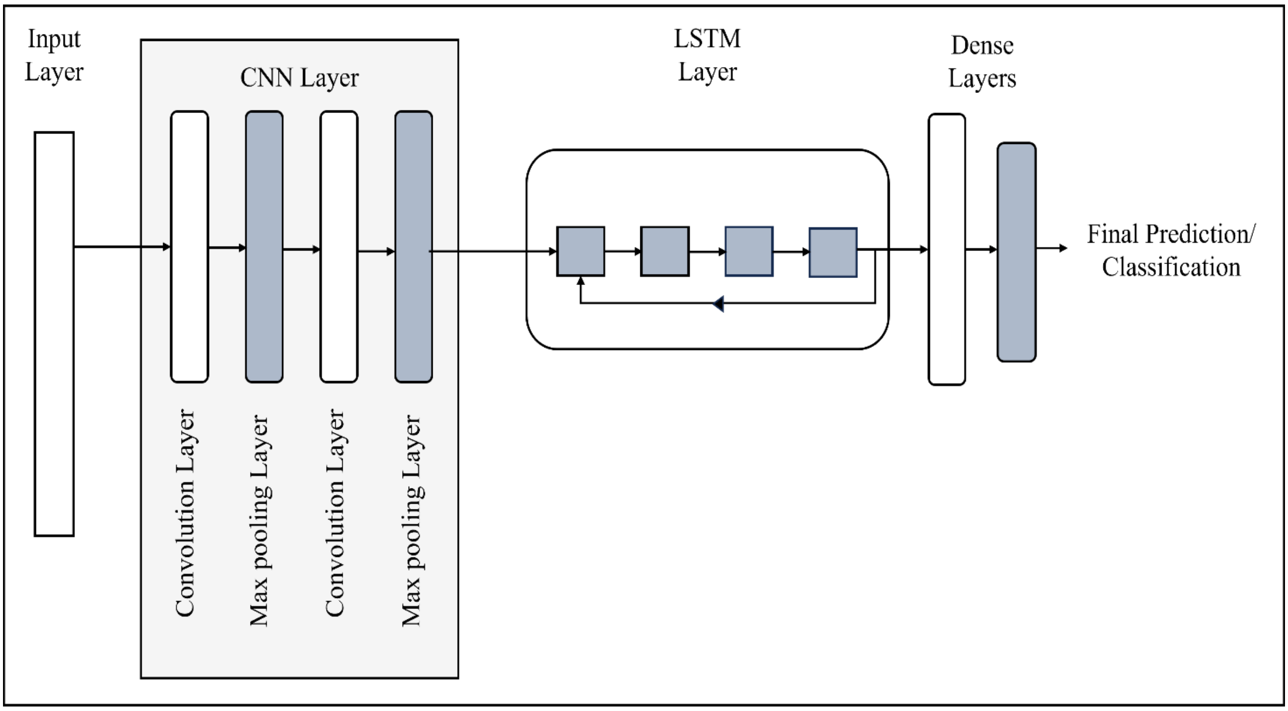

Fig. 3. Hybrid CNN–LSTM architecture for EEG signal classification.

D. Transformer and Attention-Based Models

Transformer and attention-based models represent a recent advancement in EEG signal classification. These models focus on identifying the most relevant features in EEG signals and capturing long-range dependencies.

Studies report that transformer-based models achieve classification accuracy of approximately **88% to 92%**, making them competitive with hybrid deep learning models [18], [23], [25]. Additionally, attention mechanisms improve model interpretability by highlighting important signal regions.

E. EEG Signal Preprocessing and Denoising

EEG signals are highly susceptible to noise and artifacts, which can significantly degrade classification performance. Common preprocessing techniques include filtering, normalization, and artifact removal.

Recent studies have also introduced deep learning-based denoising methods using autoencoders and CNNs, which help improve signal quality and overall system accuracy [6], [21]. Effective preprocessing is a critical step in achieving reliable BCI performance.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⪢ Peer-reviewed & Refereed journal ⪢ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.15480

F. Transfer Learning and Generalization

One of the major challenges in EEG-based BCI systems is variability across subjects and sessions. Transfer learning techniques have been introduced to improve generalization by adapting models trained on one dataset to new users. These approaches reduce the need for large labelled datasets and improve classification performance across different users, making BCI systems more practical for real-world applications [10], [24].

III. COMPARATIVE ANALYSIS OF MODELS

To better understand the performance of different AI models used in EEG-based BCI systems, a comparative analysis is presented in Table I. The comparison highlights various models, techniques, accuracy levels, advantages, and limitations based on recent research studies.

TABLE I – COMPARISON OF AI MODELS IN EEG-BASED BCI

Model	Technique Used	Accuracy (%)	Advantages	Limitations
CNN (EEGNet)	Convolutional Neural Network	80–85%	Good spatial feature extraction, efficient	Cannot capture temporal dependencies
Deep CNN	Deep learning architecture	82–87%	High accuracy, automatic feature extraction	Requires large dataset
LSTM	Recurrent Neural Network	75–85%	Captures temporal patterns effectively	High training time
CNN + LSTM	Hybrid deep learning	85–90%	Combines spatial & temporal features	Complex architecture
Transformer	Attention-based model	88–92%	Captures long-range dependencies	Computationally expensive
Autoencoder	Deep learning (unsupervised)	~80%	Effective denoising	May lose important features
Transfer Learning	Pre-trained models	82–88%	Reduces training data requirement	Limited adaptability
Hybrid Attention Model	CNN + Attention	88–91%	Improved feature focus	High complexity

The comparison shows that hybrid and transformer-based models achieve higher accuracy compared to traditional models, while also highlighting trade-offs between performance and computational complexity.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15480

IV. WORKING PRINCIPLE OF BCI

An EEG-based Brain–Computer Interface (BCI) system operates by acquiring brain signals and converting them into meaningful commands through a sequence of signal processing and machine learning steps. The overall process involves multiple stages, including signal acquisition, preprocessing, feature extraction, and classification.

Initially, **EEG signal acquisition** is performed using electrodes placed on the scalp to capture electrical activity generated by the brain. These signals are recorded as time-series data and represent different mental states or intentions of the user. The acquired signals are then passed through a **preprocessing stage**, where noise and artifacts caused by eye blinks, muscle movements, and external interference are removed. Techniques such as filtering, normalization, and artifact removal are commonly used to improve signal quality.

Next, **feature extraction** is carried out to identify relevant patterns from the EEG signals. Features such as frequency components, spatial patterns, and temporal characteristics are extracted to represent the data in a meaningful way.

Finally, the extracted features are fed into **classification models**, where machine learning or deep learning algorithms such as CNN, LSTM, and hybrid models are used to classify the signals into different categories. Based on the classification results, appropriate commands are generated to control external devices such as computers, robotic systems, or assistive technologies.

V. RESULTS AND DISCUSSION

The analysis of recent research in EEG-based Brain–Computer Interface (BCI) systems demonstrates that the integration of Artificial Intelligence (AI) and deep learning techniques has significantly improved classification performance. Models such as CNN, LSTM, and hybrid CNN–LSTM architectures have shown higher accuracy compared to traditional machine learning approaches.

CNN-based models are effective in extracting spatial features from EEG signals, achieving accuracy levels of approximately 80%–85%. However, their limitation in capturing temporal dependencies led to the development of LSTM-based models, which can process sequential data and achieve accuracy in the range of 75%–85%.

Hybrid models combining CNN and LSTM have demonstrated superior performance by leveraging both spatial and temporal feature extraction. These models achieve classification accuracy up to 90% in motor imagery tasks, making them one of the most effective approaches for EEG-based BCI systems.

Furthermore, transformer and attention-based models have recently gained attention due to their ability to capture long-range dependencies and focus on relevant features. These models achieve accuracy levels of approximately 88%–92%, making them competitive with hybrid architectures.

The comparative analysis also indicates that preprocessing techniques play a critical role in improving classification performance. Effective noise removal and feature extraction significantly enhance the accuracy of AI models. However, there is a trade-off between model complexity and real-time performance, as more advanced models require higher computational resources.

Overall, the results from various studies indicate that hybrid and attention-based models provide better performance, while lightweight CNN models are more suitable for real-time applications. The choice of model depends on the application requirements, dataset size, and computational constraints.

VI. CHALLENGES AND LIMITATIONS

Despite significant advancements in EEG-based Brain–Computer Interface (BCI) systems using Artificial Intelligence (AI), several challenges and limitations still exist that affect their practical implementation and performance.

One of the major challenges is the **noisy and non-stationary nature of EEG signals**. EEG signals are highly sensitive to external disturbances such as muscle movements, eye blinks, and environmental noise, which can degrade signal quality and reduce classification accuracy [6], [21]. Effective preprocessing and denoising techniques are required; however, excessive filtering may lead to the loss of important signal information, thereby affecting model performance.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15480

Another critical issue is **inter-subject and intra-subject variability**. EEG signals vary significantly across different individuals and even for the same individual at different times. This variability makes it difficult for models to generalize across datasets, often requiring subject-specific training and calibration [2], [10]. Consequently, the scalability and usability of BCI systems in real-world applications become limited.

The **requirement of large labeled datasets** is another major limitation in deep learning-based BCI systems. Training complex models such as CNN, LSTM, and transformer architectures requires a substantial amount of annotated data, which is difficult and expensive to collect. In many cases, limited datasets can lead to overfitting, reduced generalization, and lower classification accuracy [3], [9].

In addition, **high computational complexity** poses a challenge for real-time implementation. Deep learning models often require powerful hardware, high memory, and long training times, making them less suitable for portable and low-power BCI systems [11], [18]. This restricts their application in wearable devices and real-time assistive technologies.

Another important limitation is the **lack of interpretability of deep learning models**. Many AI-based approaches act as black-box systems, making it difficult to understand how decisions are derived. This lack of transparency is a critical concern, especially in healthcare and clinical applications where reliability and explainability are essential.

Furthermore, **real-time implementation and latency issues** remain a challenge. Many models are evaluated in controlled environments, but their performance may degrade in real-world scenarios due to delays in signal processing, feature extraction, and classification. Ensuring low-latency and high-speed processing is essential for practical deployment.

Another challenge is **hardware and device constraints**. EEG acquisition systems often require multiple electrodes and precise placement, which can be uncomfortable for users and limit long-term usability. Additionally, variations in hardware quality can affect signal consistency and overall system performance.

Finally, **ethical and privacy concerns** are emerging issues in BCI systems. Since EEG signals contain sensitive neurological information, ensuring data privacy, security, and ethical usage is crucial. Unauthorized access or misuse of brain data may lead to serious implications, highlighting the need for secure and trustworthy BCI frameworks.

VII. FUTURE SCOPE

Despite the progress in AI-based EEG BCI systems, there are several opportunities for future improvements that can enhance their performance, scalability, and real-world applicability. One of the key directions is the development of **lightweight and computationally efficient deep learning models** that can operate on low-power and portable devices. Such models would enable real-time implementation of BCI systems in wearable and assistive technologies, making them more accessible and user-friendly.

Another important area is **improving generalization across subjects**. Future research can focus on advanced transfer learning, domain adaptation, and few-shot learning techniques to develop models that perform effectively across different users without requiring extensive retraining. This would significantly improve the practicality and scalability of BCI systems in real-world environments.

The integration of **explainable artificial intelligence (XAI)** is also a promising direction. Developing interpretable and transparent models can help in understanding the decision-making process of AI systems, which is particularly important in sensitive applications such as healthcare, neurorehabilitation, and brain disorder diagnosis.

In addition, the use of **multimodal data integration** by combining EEG signals with other physiological signals such as ECG, EMG, and eye-tracking data can enhance system accuracy and reliability. Multimodal approaches can provide a more comprehensive understanding of human cognitive and physiological states, leading to improved performance in complex tasks.

Future BCI systems may also benefit from the integration of **cloud and edge computing frameworks**, which can enable faster processing, reduced latency, and efficient handling of large-scale EEG data. Edge computing, in particular, can support real-time decision-making in portable and embedded BCI devices.

Furthermore, advancements in **signal preprocessing and noise reduction techniques** are essential for improving EEG signal quality. The development of adaptive and intelligent filtering methods can help in effectively removing artifacts while preserving important signal features, thereby enhancing classification accuracy.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15480

Another promising direction is the creation of **large-scale standardized EEG datasets**. The availability of diverse and well-annotated datasets is crucial for training robust and generalizable deep learning models. Collaborative research efforts and open data initiatives can significantly contribute to this area.

Finally, future research can explore **brain–computer interface integration with emerging technologies** such as the Internet of Things (IoT), augmented reality (AR), and virtual reality (VR). These integrations can expand the application domains of BCI systems, enabling more immersive and interactive human–machine communication.

VIII. CONCLUSION

Brain–Computer Interface (BCI) systems based on Electroencephalography (EEG) have emerged as a promising technology for enabling direct communication between the human brain and external devices. The integration of Artificial Intelligence (AI) and deep learning techniques has significantly enhanced the capability of these systems by improving signal processing, feature extraction, and classification accuracy.

This paper presented a comprehensive review of recent advancements in AI-driven EEG-based BCI systems from 2020 to 2026. Various models, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), hybrid CNN–LSTM architectures, and transformer-based approaches, were analyzed in terms of their performance and effectiveness. It was observed that hybrid and attention-based models generally achieve higher accuracy by capturing both spatial and temporal features of EEG signals.

The study also highlighted several critical challenges, such as noise in EEG signals, variability across users, limited availability of labeled datasets, and high computational requirements. These challenges continue to restrict the large-scale deployment of BCI systems in real-world applications.

Overall, AI-based EEG BCI systems demonstrate significant potential in applications such as healthcare, assistive technologies, neurorehabilitation, and human–machine interaction. Future research focusing on improving model efficiency, generalization, interpretability, and real-time performance will play a crucial role in advancing this field. The continuous development of intelligent and scalable solutions is expected to make BCI systems more practical, reliable, and widely adopted in the coming years.

REFERENCES

[1]. Z. Cao, C. Lin, M. Ding, and J. Li, "Artificial intelligence for EEG-based brain–computer interfaces: A review," *IEEE Trans. Cognitive and Developmental Systems*, vol. 12, no. 4, pp. 629–642, 2020.
[2]. K. M. Hossain, M. A. Rahman, and M. S. Hossain, "Status of deep learning for EEG-based brain–computer interface applications," *Frontiers in Computational Neuroscience*, vol. 17, 2023.
[3]. X. Wang, Y. Chen, and L. Zhang, "Deep learning-based motor imagery EEG classification: A survey," *Artificial Intelligence in Medicine*, vol. 148, 2024.
[4]. L. Ma, H. Yang, and Q. Liu, "Hybrid CNN–LSTM model for EEG signal classification in motor imagery brain–computer interfaces," *Biomedical Signal Processing and Control*, vol. 89, 2024.
[5]. B. J. Edelman, J. Meng, and B. He, "Non-invasive brain–computer interfaces: State of the art and future directions," *Frontiers in Neuroscience*, vol. 19, 2025.
[6]. R. Raj, S. K. Singh, and A. Kumar, "Deep learning-based EEG denoising methods for brain–computer interface applications," *Applied Sciences*, vol. 15, no. 3, 2025.
[7]. Y. Ding *et al.*, "Neural decoding for EEG-BCI: From machine learning to deep learning," *Healthcare Engineering Science and Technology*, 2026.
[8]. A. Permata, "Hybrid deep learning framework for EEG-based BCI classification," *Proc. IEEE Conference*, 2026.
[9]. R. Lyu *et al.*, "Deep learning approaches for EEG-based healthcare and brain–computer interface applications," *Frontiers in Human Neuroscience*, 2025.
[10]. X. Y. Liu *et al.*, "Recent applications of EEG-based brain–computer interface in the medical field," *EURASIP Journal on Wireless Communications and Networking*, 2025.
[11]. T. Saichoo *et al.*, "Electroencephalography-based brain–computer interface using deep learning techniques," *Sensors*, 2026.
[12]. S. R. Moreno-Castelblanco *et al.*, "Artificial intelligence approaches for EEG signal acquisition and brain computer interface applications," *PMC*, 2025.
[13]. S. Zhang *et al.*, "A hybrid CNN–LSTM framework for harmful brain activity detection using EEG signals," *IJIRCCE*, 2025.

DOI: 10.17148/IJARCCE.2026.15480

[14]. J. Smith *et al.*, "Deep learning for EEG-based signal classification and analysis," *Scientific Reports*, 2025.
[15]. A. Kumar *et al.*, "Advanced EEG classification using hybrid deep learning techniques," *Scientific Reports*, 2025.
[16]. M. Patel *et al.*, "EEG signal classification using convolutional neural networks," *Computers, Materials & Continua*, vol. 68, no. 3, 2021.
[17]. R. Sharma *et al.*, "EEG-based BCI system using deep learning techniques," *Engineering, Technology & Applied Science Research*, 2024.
[18]. Y. Li *et al.*, "Transformer-based EEG signal classification for brain–computer interfaces," *Frontiers in Neuroscience*, 2026.
[19]. P. Gupta *et al.*, "Deep learning driven brain–computer interfaces for cognitive applications: A survey," *Academia*, 2025.
[20]. H. Chen *et al.*, "EEG-based motor imagery classification using deep neural networks," *Scientific Reports*, 2025.
[21]. M. Rahman *et al.*, "EEG signal processing and classification using machine learning approaches," *PMC*, 2023.
[22]. L. Zhao *et al.*, "Deep learning-based EEG classification using hybrid models," *Computers in Biology and Medicine*, 2025.
[23]. S. Verma *et al.*, "Attention-based deep learning models for EEG signal analysis," *ScienceDirect*, 2026.
[24]. K. Singh *et al.*, "AI-based EEG signal classification and feature extraction techniques," *Frontiers in Computational Neuroscience*, 2022.
[25]. D. Wu *et al.*, "Deep neural networks for EEG-based brain–computer interface systems," *ScienceDirect*, 2026.